Bioresource Technology 369 (2023) 128504

Contents lists available at ScienceDirect

Bioresource Technology

journal homepage: www.elsevier.com/locate/biortech

Review

Machine learning and statistical analysis for biomass torrefaction: A review

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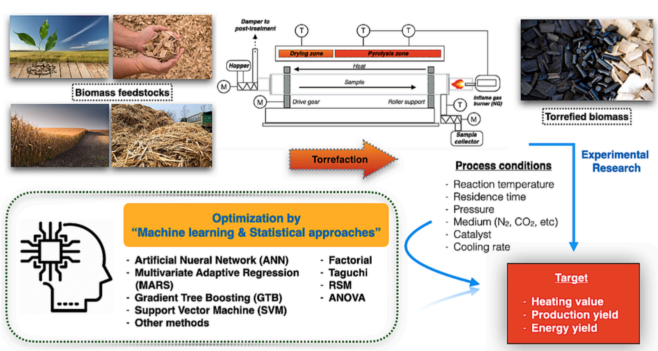
HIGHLIGHT

- Machine learning and statistical approaches are effective tools for predicting torrefaction.
- Artificial neural networks are the most used algorithm in forecasting biomass torrefaction.
- Combined theory model with machine learning enhances interpretability.
- Novel machine learning algorithms such as game theory and deep learning deserve study.

GRAPHICAL ABSTRACT



ARTICLE INFO

Keywords:
Torrefaction and biochar
Machine learning
Statistical approach
Artificial neural network (ANN)
Optimization
Response surface method (RSM)

ABSTRACT

Torrefaction is a remarkable technology in biomass-to-energy. However, biomass has several disadvantages, including hydrophilic properties, higher moisture, lower heating value, and heterogeneous properties. Many conventional approaches, such as kinetic analysis, process modeling, and computational fluid dynamics, have been used to explain torrefaction performance and characteristics. However, they may be insufficient in actual applications because of providing only some specific solutions. Machine learning (ML) and statistical approaches are powerful tools for analyzing and predicting torrefaction outcomes and even optimizing the thermal process for its utilization. This state-of-the-art review aims to present ML-assisted torrefaction. Artificial neural networks, multivariate adaptive regression splines, decision tree, support vector machine, and other methods in the literature are discussed. Statistical approaches (SAs) for torrefaction, including Taguchi, response surface methodology, and analysis of variance, are also reviewed. Overall, this review has provided valuable insights into torrefaction optimization, which is conducive to biomass upgrading for achieving net zero.

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https://doi.org/10.1016/j.biortech.2022.128504
Received 29 October 2022; Received in revised form 12 December 2022; Accepted 14 December 2022
Available online 17 December 2022

1. Introduction

Recently, global organizations have forced countries to demonstrate much greater ambition in expanding clean energy technologies resulting from the deteriorated atmospheric greenhouse effect and climate change. Renewable energy sources such as solar, hydroelectric, nuclear, and wind are optimal choices to replace fossil fuels. However, they face significant instability in their energy output, meaning the energy needs to be stored and released whenever and wherever. Bioenergy offers secure energy production and environmentally friendly pollution challenges. Biomass includes various kinds of waste, such as agricultural residues, woody biomass, beverage and food wastes, and animal manures, which are abundant for producing green fuels and chemicals (Umenweke et al., 2022).

Biomass residues can be converted into biofuels by thermochemical (torrefaction, pyrolysis, gasification, and liquefaction) and biological processes (anaerobic digestion and fermentation) (Seo et al., 2022). The biological process uses bacteria or enzymes to break down biomass into biofuels and chemicals (Brethauer & Studer, 2015). Alternatively, the thermochemical process adopts heat to transform biomass into green fuels. They can use various types of biomass materials as feedstocks, and the processes can be achieved within a short residence time without needing microorganism activity which takes a longer time (Okolie et al., 2020). Their advantages include upgrading product yield and conversion efficiency. Fig. 1 presents the classification of the thermochemical conversion processes.

Torrefaction, which is mild pyrolysis in nature, is slowly heated at 200–300 °C within an hour under oxygen-deficient or inert (N_2 or CO_2) environments to convert raw biomass into carbon-rich solid products, which is known as torrefied biomass (Chen et al., 2021d). The quality of the torrefied product has been improved in terms of higher heating value, lower atomic H/C and O/C ratio (Manatura, 2020), better grindability, and higher hydrophobicity. These properties enhance fuel quality and reduce transportation and storage costs when applied with densification (Ho et al., 2018a).

During torrefaction, various chemical reactions, thermal degradation, and mass and heat transfer co-occur and are complex (Chen et al., 2021d). This complexity requires accurate modeling for torrefaction reactor design, scale-up process, techno-economic assessment, and environmental evaluation (Okolie et al., 2021). Conventional techniques for modeling pyrolysis and torrefaction consist of thermodynamic analysis (Ascher et al., 2021), kinetic analysis (Chen et al., 2014), computational fluid dynamics (CFD) (Xiong et al., 2022), and process simulations (Manouchehrinejad & Mani, 2019). The thermodynamic analysis is simple and efficient under theoretical limitations. However, it requires a large number of assumptions, which causes it unsuitable for specific reactors in actual applications (Patra & Sheth, 2015). The kinetic analysis relies on determining complex reaction rates and still requires some assumptions. Moreover, the entire reaction mechanism may be unknown or difficult to comprehend during kinetic modeling (Bach & Chen, 2017; Lin et al., 2019). Computational fluid dynamics (CFD) models require a high computational capacity of the computer and predefined engineering parameters for accurate simulation (Chen et al., 2020). The process modeling depends on specific software (e.g., Aspen Plus), which is somewhat costly in some cases (Chein & Chen, 2021), and modeling knowledge. Thus, developing a reliable and accurate model for thermochemical conversion, especially torrefaction, is required.

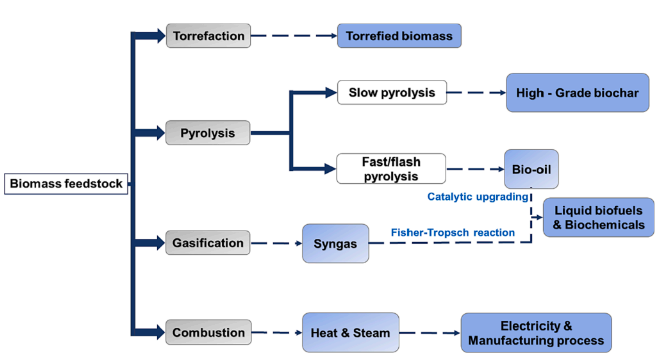

Fig. 1. The schematic of the torrefaction process compared to other thermochemical conversion routes for producing bioenergy from biomass.

Currently, ML has skyrocketed successfully in many aspects, such as medicine, business (Stokes et al., 2020), quantum chemistry (Dral, 2020), physical sciences (Mehta et al., 2019), and geoscience (Reichstein et al., 2019), biology (Kim et al., 2018) and other areas of applications progressively. It uses the principles of probability, statistics, or mathematics to analyze the patterns in a dataset and provide for forecasting the situation for inputs (Wang et al., 2022). ML works like a "black box," which means it is not involved with detailed information on reaction mechanisms and pathways of the actual processes. In contrast, conventional methods try to collect the physical and chemical phenomena during the processes. It attempts to match inputs with the corresponding outputs of the process and uses the algorithm to comprehend mathematical relationships obtained from many complex processes (Puig-Arnavat & Bruno, 2015).

Lately, the applications of ML in biological (anaerobic digestion) (Lesnik et al., 2020; Wang et al., 2020), environmental (Zhu et al., 2022), and thermochemical (pyrolysis, gasification, and hydrothermal gasification) processes for bioenergy development are attractive (Ascher et al., 2021; Umenweke et al., 2022). For example, Wang et al. (2020) used operational parameters and the dataset of the same anaerobic digestion (AD) reactor configuration from previous papers to forecast methane production values. Lesnik et al. (2020) predicted microbial fuel cells' functional resistance and resilience. However, those two works struggle with ML accuracy due to the limited data. Tang et al. (2020) predicted biomass pyrolysis's bio-oil yield and the hydrogen content in bio-oil by using linear regression and decision tree-based methods. Mutlu and Yucel (2018) applied random forests (RFs) and support vector machine (SVM) to determine syngas components for downdraft biomass gasification. The developed models have been proposed and tested with 5237 data samples using 10-fold cross-validation, and their prediction accuracy values were 89–96 %. Zhu et al. (2021a) used ML to forecast the adsorption capacity of tetracycline and sulfamethoxazole by carbon-based materials. Zhu et al. (2022) also used ML for adsorption prediction models of biochar adsorbents for wastewater treatment for pharmaceuticals and personal care products (PPCPs).

Statistical analysis is one of the methods applied to optimize thermochemical conversion and energy conversion processes (Chen et al., 2021c; Chen et al., 2022d). It includes factorial design (Chalermsinsuwan et al., 2022), Taguchi method (Chen et al., 2022b), response surface methodology (RSM) (Chen et al., 2021a), and analysis of variance (ANOVA) (Tripathi et al., 2021). The Taguchi method is commonly used in an experimental design to perform experiments and controlled processes with relatively fewer runs (Googerdchian et al., 2018). It analyses the significance of various parameters simultaneously and finds the best compositions in a controlled way (Chen et al., 2021c). RSM shows a deep understanding of optimization analysis because it shows the effect of the factors on response and the relationship of interactive factors (Chen et al., 2021a). Moreover, it shows results with visualization aspect. ANOVA is a statistical tool to determine the relative significance of various process factors that influence the performance of the system (Chen et al., 2022d). The statistical approaches will be further discussed in the following sections.

The obtained results from ML and statistical analysis can apply to the conventional techniques for modeling the torrefaction system. The output responses and simplified models can be integrated with thermodynamic analysis, kinetic analysis, computational fluid dynamics (CFD), and process simulations to predict the obtained phenomena with reduced computational cost and time. According to the above, a systematic review on torrefaction using ML is still lacking. To the authors' knowledge, this work is the first review aiming to offer comprehensive and state-of-the-art ML models in torrefaction. Moreover, statical approaches are included to cover a wide range of torrefaction. In section 2, biomass thermochemical processes are presented. Section 3 shows ML-assisted torrefaction. Section 4 discusses the statistical approach for torrefaction. Section 5 discusses challenges and future perspectives for torrefaction. Finally, section 6 summarizes essential findings from the review. Fig. 2 illustrates a concept of machine learning and statistical approaches for torrefaction in this review.

2. Biomass thermochemical conversion

Thermal-conversion process of waste biomass towards biofuels and bioenergy is traditionally classified into five main categories: torrefaction, pyrolysis, gasification, combustion, and liquefaction. Different thermal processing plays a significant role in various products (Ubando et al., 2022; Ubando et al., 2020). Torrefaction, pyrolysis, and gasification are commonly used thermal pathways to transform waste biomass into various forms of biofuel (Chan et al., 2019; Rajabi Hamedani et al., 2019; Uzoejinwa et al., 2018).

Torrefaction is known as a low-temperature pyrolysis process, which is generally used for biomass pretreatment to upgrade the fuel characteristics of biomass (i.e., *moisture, fragility, and energy density*) for use as a high-potential biofuel at a pleasant working-pyrolysis condition. This process can produce a solid product, namely, torrefied biomass, with characteristics close to lignite or coal (Pang, 2019). In contrast, pyrolysis is carried out at mild temperature conditions, typically from 400 to 700 °C. It mainly converts biomass feedstocks into biochar and simultaneously produces liquid and gas products. The operation with a high ramping rate and rapid vapor condensation during pyrolysis is suitable for making bio-oil or biocrude (Fatehi et al., 2021; Methner et al., 2022; Sankaran et al., 2020). Gasification is a leading technology for producing combustible gas fuel, especially H_2 and CO (called synthesis gas or syngas) gas products. Though combustion is also a crucial thermochemical conversion process, the primary product is heat rather than biofuels. The combustion of biomass feedstocks is directly used by burning or co-firing processes in heat, steam, and even electricity generation, which is popularly applied for the actual process in industries to minimize the CO_2 emission released from the consumption of fossil fuels. Nonetheless, releasing NO_x during real operations should be concerned with environmental issues (Fang et al., 2021; Zaman & Ghosh, 2021). Table 1 summarizes different thermochemical conversions, including torrefaction, pyrolysis, gasification, combustion, and wet conversion processes.

To date, the conversion of biomass residuals for bioenergy applications has strong potential to become a green energy resource for solving the surrounding environmental issues from fossil consumption. The production of biofuel commonly involves a thermal process, which occurs through the development of the atomic structure of raw biomass feedstocks under the influence of heat and a gaseous environment, resulting in carbon-rich products, which are called biofuels. Consequently, the torrefaction process has been thoroughly discussed and compared to the other thermochemical conversions for bioenergy utilization from biomass (Fig. 1).

2.1. Torrefaction

Through thermal decomposition, biomass torrefaction is used to improve fuel characteristics by decomposing the chemical structure of raw feedstock, especially in hemicelluloses. This process is conducted at the low-temperature condition of<320 °C under the absence of oxygen or partial oxidizing surrounding atmosphere, with regular operation times of several minutes to a few hours. The achievement of torrefaction is specifically reducing the moisture content and other oxygenated compounds by dehydration and decarboxylation reactions, resulting in an increase in heating value. In the torrefaction mechanism, biomass undergoes depolymerization by the thermal conversion process. The torrefaction degree or severity significantly depends on the temperature and holding time of the operation (He et al., 2022). Recently, lignocellulosic biomass torrefaction has received great attention for converting raw feedstock into high-quality solid biofuel. The torrefaction of lignocellulosic materials commonly involves two continual steps, including high-temperature drying followed by hemicellulose thermodegradation, lowering the product's oxygen content, which is an initial stage of thermal decomposition of lignocellulosic materials (Wan et al., 2020). This directly aims to enhance the whole fuel properties by minimizing oxygen-to-carbon (O/C) and hydrogen-to-carbon (H/C) ratios (Ho et al., 2018b; Zhu et al., 2021b). Setkit et al. (2021) conducted several torrefaction experiments on *Leucaena* wood pellets. The production yield was about 54.5 %, while the energy yield of the torrefied product was approximately 84.4 % at the torrefaction temperature of 300 °C with a torrefied period of 30 min. The results showed that devolatilization during torrefaction became more reactive at higher reaction temperatures and holding time. Also, the appearance density and grindability of the torrefied product are rectified simultaneously. Another prominence of torrefaction is the enhancement of the material's hydrophobicity. This prevents moisture adsorption when stored outside and enhances

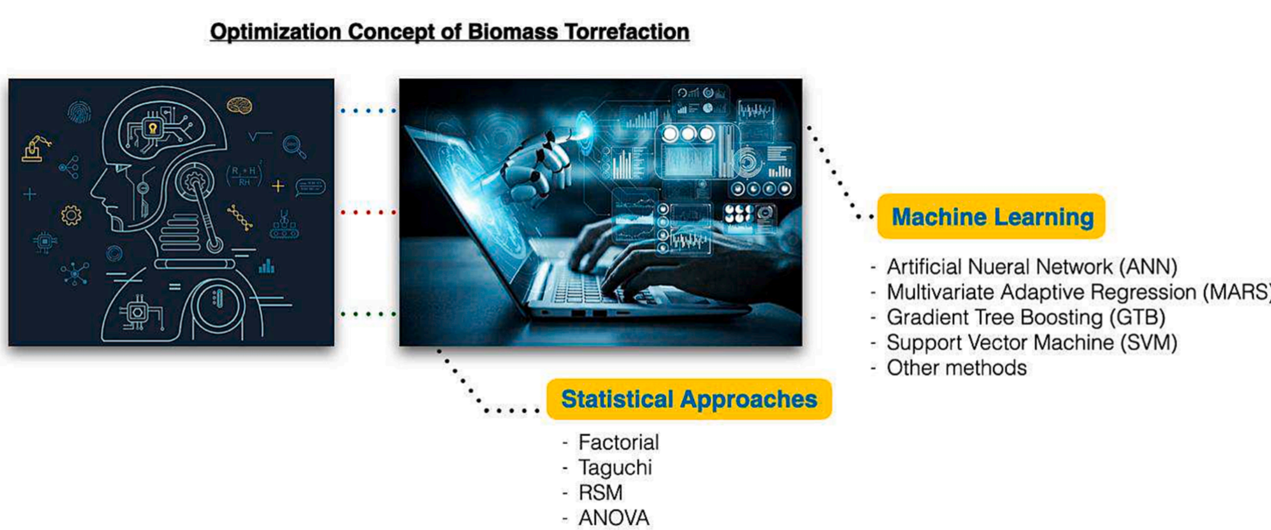

Fig. 2. Concept of the machine learning and statistical approaches in torrefaction.

Table 1
Process variables for different thermochemical conversions.

Process	Temperature (°C)	Time (min)	Heating rate (°C/min)	Other conditions	Product yield (%)
Torrefaction	200–300	5–120	<30	Inert or partial oxidation and ambient pressure	~60–95 for torrefied biomass
Pyrolysis	400–900	30–480	5–1,000 (fast pyrolysis)	Inert environment and ambient pressure	< 40 for solid char
					40–95 for bio-oil (fast pyrolysis)
Gasification	>700	<60	Not significant	Air/partial air and ambient pressure	> 70 for syngas

Source: Modified from Zhang et al. (2018); Zhang et al. (2020); Kamal Baharin et al. (2020); Setkit et al. (2021).

product durability (Aniza et al., 2022).

The literature has demonstrated that the typical calorific value of biomass with varied operating conditions is raised by approximately 5–30 % after torrefaction (Chen et al., 2019; Gan et al., 2020). Lately, torrefied biomass has been used to substitute the traditional natural coal feedstock in heat and power generation through gasification, co-firing combustion, or direct combustion, to minimize the CO_2 emission released from the process. Nonetheless, increasing holding time and temperature during torrefaction has been implemented to reduce moisture and volatile contents due to thermal decomposition, leading to the carbon content of torrefied products (Gan et al., 2020; Gan et al., 2018). In addition, torrefaction has been widely investigated for the pretreatment process for carbon material manufacturing, such as bio-coal and activated carbon, which can be improved low-quality raw biomass into a promising feedstock for further utilization (Wang et al., 2018). Technically, the critical challenges for biomass torrefaction technologies are involved the post-treatment system for gas and other contaminant products, scaling up of operation, process heat integration, and predictability and consistency of torrefied products. In fact, the torrefaction variables significantly control the quality of the torrefied product, as shown in Table 2. For instance, in one case, the torrefaction temperature has a dominant impact on product characteristics, such as color-changed appearance, production yield, and heating value (Chen et al., 2018).

2.2. Pyrolysis

The pyrolysis of biomass is typically classified into slow pyrolysis (which is the primary process for char production) and fast pyrolysis (producing a significant product as a bio-oil or biocrude (Foong et al., 2020). However, pyrolysis reaction is an initial reaction step in combustion or gasification. The difference between slow and fast or flash pyrolysis is commonly separated by ramping rate, how fast heat is transferred to biomass interior, temperature, and operation time. All factors have been used to diversify the product contributions (Zhang et al., 2020). Mild heating rates with long operation times in pyrolysis (slow or intermediate pyrolysis) exhibit a high proportion of char, approximately 20–40 % as production yield. Biomass pyrolysis for biochar or solid carbon materials mainly utilizes woody biomass (e.g., wood chip, bark, forest residue, and sawdust), agricultural wastes (e.g., fruit shells, corn stems, fruit peels), and municipal solid wastes (e.g., waste tires, MDF solid waste, plastic waste) as raw materials (Hassan et al., 2020).

Table 2
Process variables for thermochemical conversion for biomass.

Thermal pretreatments	Process variables	Characteristics
Dry Torrefaction	• Temperature Residence time Oxidative agent concentration Feedstock particle size Reactor type	• Temperature ranges: 200–300 °CMedia: Inert gas/Partial oxidative gas (N_2/ CO_2) Pressure: atmospheric pressure Cooling process: N_2 flowing/ indirect water cooling
Prolysis	• Temperature Residence time Feedstock particle size Reactor type	• Temperature ranges: >400 °CMedia: Inert gas (N_2/ Ar) Pressure: atmospheric pressure Cooling process: N_2 flowing/ indirect water cooling
Gasification	• Equivalence ratio, ER ratio Oxidative agent Feedstock particle size Reactor type	• ER ratio: 0.1–0.5 Temperature ranges: 550–1000 °C Media: Air, steam, CO_2 Catalysts Purification unit

Source: Modified from Chan et al. (2019); Chen et al. (2019); Sankaran et al. (2020).

On the other hand, pyrolysis conducted with rapid heating rates of the feed yields high amounts of condensable vapors (50–75 %), reaching the bio-oil or biocrude product (Dharmaraj et al., 2021). The bio-oil chemical composition is complex, mainly composed of aromatic hydrocarbons, anhydrous sugar, acids, alcohols, esters, ketones, and water. The traditional bio-oil without any purifications has higher oxygen content and lower heating value when compared to commonly available liquid fuels (i.e., fuel oil, diesel, and gasoline) (Zhang et al., 2018). The lack of fuel qualification for bio-oil is mainly caused by water. Various oxygenated compounds in the bio-oil cause its calorific value lower (Boubacar Laougé et al., 2020**)**. Additionally, some oxygenated compounds, especially acids, which often have a pH value of 2–4, contained in bio-oil also exhibit serious shortcomings, such as product stability and even equipment corrosion, by directly utilizing bio-oil (Park et al., 2019).

2.3. Gasification

Gasification is a thermal process to transform solid fuels like natural coal into gaseous fuel products, called synthetic gas or syngas, mainly consisting of CO and H_2. Biomass provides unique advantages, such as sustainability, renewability, low carbon emission, and managing and reducing waste (Kumar Sharma et al., 2021). In biomass gasification, several biomass feedstocks, such as forest residues, agricultural by-products, municipal solid wastes, and sewage sludge, become alternative resources for producing syngas. Biomass gasification often occurs at high-temperature conditions between 800 °C and 1500 °C with a partially limited proportion of carrier gas (e.g., air, steam, O_2, or CO_2). Nonetheless, a small proportion of biochar, bio-oil, and even tar from biomass gasification aside from a significant product, syngas (Tushar et al., 2020).

Waste biomass or other organic substances is necessary to produce syngas as an alternative feedstock. However, the syngas product can be refined into other liquid biofuels and biochemicals through Fisher-Tropsch synthesis (Gruber et al., 2019). Regarding gasification operation variables, they significantly occur in different reaction mechanisms such as drying, pyrolysis, partial combustion, and reduction, simultaneously indicating that the desired product contribution and quality of syngas can be adjusted by fine-tuning the operation parameters (Hwang et al., 2021).

2.4. Combustion

Traditionally, biomass combustion is used for the production of heat and power. Fossil fuels have supplied most of the world's energy consumption due to their abundance, high-energy density, and simple handling during operation (Chen et al., 2022e; Sankaran et al., 2020). However, great attention has recently been focused on the CO2 emissions that have caused severe global warming. The use of biomass is CO_2-neutral or carbon sequestration due to the photosynthesis showing that CO_2 is directly adsorbed and converted during biomass growth (Yi et al., 2018). Therefore, using biomass as a solid fuel for combustion is a good alternative energy resource for industrialized applications. In addition, air pollutants, such as NO_x and SO_x, may be reduced by using biomass to generate heat and power (Osman, 2020). The substitution of biomass from coal and petroleum fuels for combustion has gradually increased in industrial utilizations worldwide. Table 3 displays the optimal conditions of different thermochemical conversions for biofuel production at different operating conditions.

3. Machine learning

Machine learning (ML) is a subclass of artificial intelligence (AI), a technology that enables a machine to learn human wisdom (Chen et al., 2022a). ML works by learning proper structures between input data and its output. Used data in training is named the training dataset for the model. Then, the trained model is confirmed by validation, which is repeatedly trained until the model reaches the required criteria. The trained structure creates a rule for supporting the forecast of testing data (output data).

ML includes four algorithms: supervised, unsupervised, semi-supervised, and reinforced learning (Ascher et al., 2021). The input and output data are chosen for the model in supervised learning. After that, the model will learn to match input data with its output data (Guan et al., 2022). Finally, the ML model predicts output with an identified input. The actual data then validate the predicted results (output) to reduce the gap between the actual and modeled output. It is noted that the size and features of the database are essential to use supervised learning effectively (Guan et al., 2022). Regression and classification methods are two types of supervised learning. The regression focuses on searching for the best proper relation between the input and output data (Wang et al., 2021), while the classification aims to evaluate phenomena of patterns between datasets. It can be observed that even though both algorithms are used in ML, they still have different purposes in applications.

On the other hand, unsupervised learning attempts to discover the hidden formats or information in unlabeled data without the aim of finding the data needed. It can be divided into clustering and dimensionality reduction (association). Clustering deals with grouping the structure or pattern into a cluster. For example, the patterns with the most similarities keep in a group and have fewer or no similarities with the patterns of another group. The dimensionality reduction is used for seeking the connection between factors in the extensive database. Consequently, it evaluates the items that arise together (Umenweke et al., 2022).

The semi-supervised learning acts between supervised and unsupervised learning algorithms. It integrates the labeled and unlabeled datasets during the training period. It supports the labeled data of supervised learning in cases of challenging and time-consuming (Guan et al., 2022). In reinforcement learning (RL), the RL algorithm (agent) learns the relationships between input and output by interacting with an environment. Unlike supervised learning, the agent learns automatically using feedback without labeled data. It obtains the feedback from its own system simultaneously, where the last action will control the following action to reach maximum rewards. Fig. 3 shows an overview of the ML algorithms.

Seven common ML algorithms have been used to model torrefaction processes. They are multivariate adaptive regression splines (MARS), artificial neural networks (ANNs), tree family (e.g., gradient tree boosting (GTB), decision tree (DT), random forest (RF)), support vector machines (SVMs) and adaptive neuro-fuzzy inference system (ANFIS). These data were obtained from the "Scopus" and "Web of Science" databases when using "machine learning torrefaction" as the keyword. ANNs are the most used in torrefaction (27 %), followed by MARS (20 %), GTB (13 %), RF (13 %), SVMs (13 %), and ANFIS and DT for the rest. Few publications (7 papers) published since 2019 were noticed. It is noted that 5 papers (70 %) in 2022 have been published, which means using ML-cooperated with torrefaction is receiving attention for research.

Table 4 shows an overview of the publications using the ML-assisted torrefaction process. It can be observed that studies related to ML for both dry and wet torrefaction are still limited. Lignocellulosic biomass is the mandatory feedstock residue for the prediction. Microalgae, macroalgae, and distilled residues are becoming interesting. Generally, the input data include feedstock properties, torrefaction operating conditions, and reactors properties (Onsree & Tippayawong, 2021). The feedstock properties comprise proximate analysis, ultimate analysis, fiber analysis (hemicelluloses, celluloses, lignins, etc.), and composition analysis (carbohydrates, proteins, lipids, etc.). At the same time, mostly the output data are solid yield and their corresponding HHV of the biochar (Kartal & Özveren, 2022b). The models achieved an acceptance prediction with a higher coefficient of determination R^2 ($R^2 > 0.9$).

In summary, ML is an emerging technology in torrefaction. It allows higher accuracy and valuable data-based decisions for complex problems. A variety of input features has been used to envision interesting

Table 3
Optimal conditions for biomass thermochemical conversions.

Raw biomass	Conversion process	Process conditions	Process performance	References
Coffee ground residue	Torrefaction (Torrefied product)	200 °C for 15 min, N_2 atmosphere	98.20 % of MY, 98.93 % of EY for torrefied biomass	Ho et al. (2018b)
Microalgae residue	Torrefaction (Torrefied product)	200 °C for 15 min, N_2 atmosphere	92.41 % of MY, 92.62 % of EY for torrefied biomass	Ho et al. (2018b)
Leucaena wood pellet	Torrefaction (Torrefied product)	300 °C with 30 min, N_2 atmosphere of 150 ml/min, Heating rate 0f 10 K/min	54.5 % of MY, 84.4 % of EY for torrefied pellet	Setkit et al. (2021)
Distilled spirit residues	Flue gas torrefaction (Torrefied product)	200 °C with 30 min, Flue gas atmosphere (0.8 % O_2) of 150 ml/min	15.74 MJ/kg of HHV (Raw mat. = 13.91 MJ/kg) Torrefied biomass	Zhu et al. (2021b)
Wheat straw	Slow pyrolysis (Biochar product)	600 °C with 60 min using 100 ml/min N_2 flow	31.55 % MY, and Fixed carbon of 65.34 wt% of biochar	Zhang et al. (2020)
Rice husk	Fast pyrolysis (Bio-oil product)	550 °C with 30 min using 200 ml/min N_2 flow, Heating rate > 1000 K/min (drop tube reactor)	~38 % MY for bio-oil product	Zhang et al. (2018)
Dried glass	Gasification (Syngas product)	Air-steam atmosphere using equivalent (ER.) ratio of 0.23, steam and biomass ratio of 1.56 at 800 °C, feeding rate 0.5 Nm^3/kg (Fluidized bed gasifier)	HHV_{gas} of 5.73 MJ/Nm^3, 31.44 of H_2 and 40.06 CO in syngas product (%vol)	Cao et al. (2021)

Note: MY: mass yield; EY: Energy yield; HHV: higher heating value.

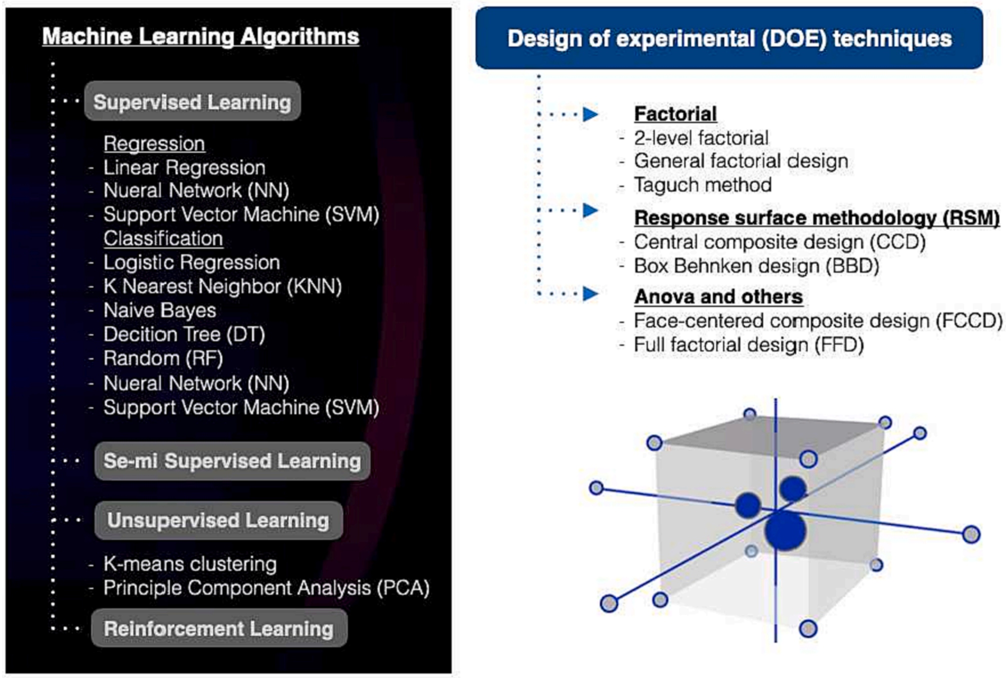

Fig. 3. Overview of ML algorithms and statistical approaches to biomass torrefaction.

Table 4
Summary of ML models used for the modeling of torrefaction.

ML model	Feedstock	Parameters	Size data set	Prediction Performance	Main finding	References
SVM, MARS, RF	Woody biomass	• IP: FC, VM, T, t, O/C, H/C OP: HHV of torrefied biomass	300	R^2 of RF-SA, MARS-SA, and SVM-SA are 0.63, 0.82, and 0.90, respectively	• SVM-SA is good for determining the HHV FC is the most significant factor for evaluating the HHV	Nieto et al. (2019)
GTB, KRR	Lignocellulosic biomass	• IP: MC, VM, A, C, H, N, O, SZ, T, t, CO_2, O_2, N_2 OP: SY	800	R^2 of KRR and GTB are 0.90 and 0.07, respectively	• GTB had the highest precision. Temperature is the most influential factor for predicting yield. VM and H showed an opposite trend with C.	Onsree and Tippayawong (2021)
ANN	Lignocellulosic biomass	• IP: T, t, FC, VM, A OP: Chemical exergy of torrefied biomass	284	R^2 of ANN was>0.92	• ANN offers an indirect method for predicting the chemical exergy of torrefied biomass.	Kartal and Özveren (2022a)
ANN, ANFIS	Lignocellulosic biomass	• IP: FC, VM, A, T, t OP: C, H, O and HHV of torrefied biomass	448	R^2 of ANN and ANFIS for HHV are 0.8850 and 0.8321, respectively.	• ANN showed better results than ANFIS.	Kartal and Özveren (2022b)
MARS, ANN	microalgal residues, spent coffee grounds, and Chinese medicine residue	• IP: feedstock type, temperature, and duration OP: TSI	1626	R^2 of MARS and ANN are 0.9851 and 0.9784, respectively.	• MARS identifies temperature as the most influential factor on TSI.	Chen et al. (2022a)
MARS, ANN, DT	microalgal and macroalgal residues, sorghum distillery residue	• IP: feedstock, classification, MC, A VM, FC, C, H, O, N, T, t, H_2SO_4 OP: Glucose concentration	49	R^2 of NN and MARS are 0.996 and 0.929, respectively	• The predicted highest glucose concentration is 15.216 g·L^{-1}.	Chen et al. (2022c)
GTB, RF, SVM, SHAP	Lignocellulosic biomass	• IP: T, t, N_2, CO_2, O_2, SZ, SM, MC, VM, FC, A, C, H, O, N, S, H/C, O/C, Hm, Ce, Lg OP: SY, HHV	410	R^2 of GTB for SY and HHV are 0.93 and 0.91, respectively	• Operating conditions are the most influential for the torrefaction. Torrefaction reactor properties are equally important with biomass characteristics.	Onsree et al. (2022)

Note: A = Ash, ANFIS = adaptive neuro-fuzzy inference system, ANN = artificial neural network, DT = Decision tree, IP = Input parameter, OP = Output parameter, Ce = Cellulose, FC = Fixed carbon, GTB = Gradient tree boosting, Hm = Hemicellulose, KRR = Kernel ridge regression, Lg = Lignin, MC = moisture content, MARS = Multivariate adaptive regression splines, RF = Random forest, SA = Simulated annealing, SHAP = Shapley additive explanation, SVM = Support vector machine, SY = Solid yield, SZ = Sample size, T = Torrefaction temperature, TSI = Torrefaction severity index, t = residence time, VM = volatile matter.

output factors. Torrefaction is an upstream process prior to the primary thermo-chemical process (pyrolysis, gasification, and combustion). ML enables to make the process to be more efficient in terms of energy, environmental and economic optimization. The following subsections provide brief descriptions of the ML methods.

3.1. Artificial neural networks (ANNs)

ANNs are the most famous type of ML used for modeling gasification and pyrolysis (Ascher et al., 2021). It is also used for torrefaction lately. ANN has a very high capability to learn nonlinear relationships between inputs and outputs.

Kartal and Özveren (2022a) used ANN to foretell torrefied biomass's chemical exergy employing their raw proximate analysis and torrefaction conditions. The ANN model showed an acceptable result with a higher R^2 value (0.92). Kartal and Özveren (2022b) also developed ANN and ANFIS to determine the elements C, H, and O and HHV of torrefied biomass from observing the raw proximate analysis and torrefaction conditions as in the previous work. They indicated that the ANN model showed better efficiency than ANFIS. Although remarkable model results were performed, the torrefaction performance factors such as solid yield and energy yield were not studied with those input factors.

Aniza et al. (2022) also used ANNs combined with the Taguchi method for torrefaction and pyrolysis of the spent mushroom substrate via microwave irradiation. This study predicted the yield of biochar and bio-oil from input factors (catalyst, particle size, magnetic agent, and power). They found a quick propagation algorithm of ANN showed excellent R^2 (0.9998–0.9999).

In summary, the ANN is most often used among the ML algorithms in biomass torrefaction. However, its black box behavior led to unclear comprehension of the torrefaction process. Thus, combining thermodynamic-kinetic modeling or optimization techniques with ANN may increase interpretability (Aniza et al., 2022; Safarian et al., 2020).

3.2. Multivariate adaptive regression splines (MARS)

MARS was presented by Friedman Friedman (1991) and used a few variables to analyze data (Wen et al., 2020). Flexible and efficient models bond a given predicted value and a set of predictive factors. It can predict values from the provided dataset and establish the nonlinear relationship between them.

Chen et al. (2022a) developed ANN and MARS to foretell the torrefaction severity index (TSI). Torrefied Chinese medicine residue, used coffee grounds, and microalgae residues were used for the study. As input parameters, the datasets were extended with torrefaction temperatures and residence times. The results indicated that the prediction accuracy of MARS ($R^2 = 0.9851$) was better than that of ANN ($R^2 = 0.9784$) in determining the TSI. The temperature was the most significant parameter in determining TSI, followed by duration time and feedstock type from the MARS predictions. The lower precision of the ANN may upgrade by increasing the variety of the input parameters and the number of hidden layers and neurons.

Chen et al. (2022c) also performed MARS, NN, and DT to predict glucose concentrations in wet torrefaction from microalgae, macroalgae, and sorghum distillery residue (SDR). Forty-nine (49) datasets were employed to train and test data with portion 7:4. The predicted results of NN ($R^2 = 0.9999$) were better than those of MARS ($R^2 = 0.9154$). The lower accuracy of MAR was found due to the lower four parameters that were analyzed. More parameters may improve the accuracy.

3.3. Gradient tree boosting (GTB)

GTB is a popular ML algorithm. It is a potential technique for the constructive model in the form of a set of failed prediction models (Friedman, 2001). It operates by learning mistakes from the previous learner models and creating the corrected prediction for the final model. Onsree and Tippayawong (2021) developed GTB and Kernel ridge regression (KRR) to predict the solid yield of biochar from proximate analysis, elemental analysis, and torrefaction conditions. The GTB showed a maximum accuracy value (R^2) of almost 0.90. However, the accuracy could be higher if more input factors were considered.

3.4. Support vector machine (SVM) and other ML algorithms

SVM is a supervised learning algorithm used for regression and classification problems. SVM attempts to make the best line to separate *n*-dimensional space into classes. This allows us to easily put the new data stage in the right class in the future.

Nieto et al. (2019) conducted a combined SA and SVM (SVM–SA), MARS, and RF model to predict torrefied biomass's HHV from the input factors, including operational condition (temperature and duration time) and proximate and elemental analyses. The SVM–SA considerably enhances the prediction performance compared with that obtained from only an SVM. It can be noted that the solid yield and energy yield were not considered.

Onsree et al. (2022) used GTB, RF, and SVM, combined with Shapley additive explanation (SHAP), to predict torrefied biomass's HHV and SY. Twenty-two inputs, including feedstocks' proximate and elemental analyses, lignocellulosic contents, and torrefaction characteristics, were considered. The GTB model presented the yield and HHV of torrefied biomass with higher R^2 (>0.9) and very low overall error (<3%). The ML model could be explicitly and generally interpreted with the SHAP technique.

4. Statistical approach to biomass torrefaction

Biomass plays a significant role in developing an alternative to fossil fuels because it is a sustainable energy source. This means biomass can cut greenhouse gas emissions from the balance of carbon emission and removal. Moreover, biomass is abundant worldwide, readily available, and relatively less expensive (Neville, 2011; Tursi, 2019). The main advantage of biomass is the reduction of harmful emissions (e.g., air pollutants and greenhouse gases) caused by non-renewable fuels (Gong et al., 2019). Moreover, biomass has a chemical composition with great potential to be converted into solid, liquid, and gaseous products with higher added value (Bridgwater, 2012; Natarajan et al., 2018). However, the use of biomass as solid biofuels is limited by its hygroscopicity, low energy density, high oxygen content, and a high degree of inhomogeneity compared to conventional fuels (Chen et al., 2015; Lam et al., 2012). These properties lead to low process efficiency and high transportation, handling, and storage costs. Thus, the proper refinery approaches and upgrading methods have been explored to dispel the drawbacks and increase the quality of the product formed (Hilten et al., 2010; Robbins et al., 2012; Uslu et al., 2008).

Conventional experiments, where one factor is varied while the others remain constant, are still used in most torrefaction works. The variation of multiple factors is usually found in some experimental research. Operating parameters, for example, duration, temperature, heating rate, and particle size, along with biomass components (cellulose, hemicelluloses, and lignin), have significant influences on the product properties (Chen & Kuo, 2011; Medic et al., 2010; Mundike et al., 2016; Strandberg et al., 2015). Moreover, the interaction effect of independent variables is difficult to consider. Therefore, statistical approaches such as factorial and response surface methodology (RSM) are proposed to investigate the factors affecting torrefaction and their interactive behavior to obtain an optimal response (Buratti et al., 2018; Lee et al., 2012; Lee & Lee, 2014).

Fig. 3 shows statistical approaches to biomass torrefaction, including factorial and response surface methodology. The statistical methods that can be applied to biomass torrefaction study include factorial, response surface methodology (RSM), and analysis of variance (ANOVA). The factorial is a simple experimental setup that consists of multiple factors and their separate and conjoined influence on the subject of interest in the experiment. The benefit of a factorial design is that it allows looking at multiple levels at a time and how the factors influence the response. For the response surface methodology and the other statistical methods, the main idea is to use a sequence of designed experiments to obtain an optimal response with a higher degree than the factorial. In addition, the analysis of variance can be performed to examine the adequacy and fitness of the predicted models. It is a collection of statistical models and their associated estimations to analyze the differences among response means. Then, the significant parameters are selected based on the ANOVA results.

Table 5 concludes the statistical experimental design used for the modeling of torrefaction. From the literature, various biomass types were considered to explore the effects of torrefied factors such as temperature, residence time, and biomass properties. The considered output variables were mainly solid yield, calorific value, weight loss, and the energy yield of torrefied samples. However, the previous literature results were illustrated and explained based on their biomass types. Therefore, in this study, all the relevant results are summarized and discussed based on each used statistical method. The obtained knowledge, such as the general effect of each input parameter and the relative importance of each input parameter, can help scientists and engineers design and operate the torrefaction system to reach the desired system objective.

4.1. Factorial

Factorial or screening design can efficiently examine several variables' effects and their impact on a response simultaneously. Experiments are often designed to determine the effect of one variable upon one response. Factorial design can be used to find each factor's influence on the response variable and the impact of the interaction between factors on the response variable. It accurately performs when the variables' interaction is solid, and every variable contributes markedly.

4.1.1. Two-level factorial

The simplest factorial design is the two-level factorial design. In this design, each factor has two levels (2^2), and experiments are practiced at the possible combination of the two levels. These designs can evaluate the influences of all the factors on outcomes and their interactions, which often proves to be the key to comprehending a process. Compared to other designs, the merit of the two-factor study is the reduction in experimental runs to obtain the same precision.

Abreu-Naranjo et al. (2018) used a two-level factorial experimental design to identify the effects of the two factors (i.e., torrefaction duration and temperature) on the solid yield and calorific value of torrefied *Dichrostachys cinerea* wood. The results showed that both studied factors and their interaction significantly involved solid yield, and temperature affected the increment in high heating value (HHV) more than residence time. These two response variables exhibited an excellent linear relationship with the coefficient of determination (R^2) values>95 % in each case. de Oliveira Brotto et al. (2022) also presented the results from statistical analysis of the torrefaction process by two-level factorial design with a significance interval of 95 %. The effects of temperature and duration and the interaction between the two parameters on the mass yield of the torrefied sample were investigated. The statistical model was suitable for predicting the response values with a good R^2 of 0.99, implying that the model was relevant to the results. Moreover, the factors' temperatures and residence times were found to be important in addition to their interaction. Residence time had the strongest effect on mass yield in torrefaction, followed by temperature and the interaction of the two factors. Additionally, combining short residence times with high temperatures or long residence times with low temperatures was better for obtaining satisfactory mass yields.

4.1.2. General factorial design

The model and analysis of multi-way factorial are a generalization of two-way factorial. Madanayake et al. (2016) used a 5-level factorial experimental design for *J. curcas* seed cake torrefaction. Their regression analysis showed a linear fit (R^2 was around 92 %). Both temperature and time independently affected three responses: solid and energy yields and HHV. However, the two factors' interaction was not pronounced. The torrefaction temperature was a more dominant factor compared to the duration.

Rudolfsson et al. (2015) conducted a parametric study by combining biomass torrefaction and pelletization using a five-level fractional factorial design. Qualitative parameters include torrefaction temperature, moisture content, particle size, and pelletizing temperature. All parameters tested were shown to significantly influence friction work and compression work, as well as pellet dimensions and strength. Then, Rudolfsson et al. (2017) used a five-level fractional factorial design to study a combined semi-industrial scale torrefaction and pelletization. The two key parameters (torrefaction and pelletization) parameters were investigated individually and simultaneously. The influence of the factors on the studied responses was ranked by torrefaction temperature > torrefaction time > moisture contents > press channel lengths. Moreover, the interactions of each input variable also affected the investigated output variables.

4.1.3. Taguchi method

The Taguchi experimental design is a suitable statistically designed experiment for several chemical engineering applications (Chen et al., 2021b). The Taguchi approach can also identify the influence order based on input variables' contribution to the response factor. Moreover, experimental runs are reduced with this approach while providing similar results.

Arpia et al. (2021) designed microwave torrefaction experiments of sugarcane bagasse using the Taguchi method. The influences of the three control parameters (microwave power, duration, and catalyst concentration) with various levels on the energy yield response were compared by calculating the effect value of each parameter. Microwave power was found to have the most decisive influence on the energy yield, whereas duration and CaO concentration has minor effects. Moreover, the heating value of the raw feedstock was also improved.

Chen et al. (2022d) also employed Taguchi experimental design to investigate the effects of duration, microwave power, and catalyst concentration on the energy yield of a microalga under catalytic microwave torrefaction. The results indicated that microwave power was the deterministic parameter. The catalyst concentration was the second influential factor, and duration only had a slight effect. The highest upgrading energy index (UEI) value was achieved under the combination of minimum microwave power, minimum torrefaction time, and maximum catalyst concentration.

4.2. Response surface methodology (RSM)

Response surface methodology combines statistical and mathematical techniques according to the polynomial-equation-expressed correlation of experimental data set for predicting the response behavior based on various process input variables. The significant advantage of RSM is to provide a minimum number of required experimental runs in forecasting the optimal condition with the comprehensive consideration of all the parameters. The predictive mathematical model is generated, which indicates the interactions between various influence variables and one or more output variables. This method can be used to address a wide range of research issues. The experiment can be designed using Box-Behnken design (BBD) and central composite design (CCD) (Chen et al., 2022d).

4.2.1. Central composite design (CCD)

In statistically designed experiments, central composite design (CCD)

Table 5
Summary of statistical experimental design used for the modeling of torrefaction.

DOE techniques	Feedstock	Parameters	Main finding	References
2-level factorial	*Dichrostachys cinerea* wood	• IP: torrefaction temperature, reaction time OP: solid yield, HHV of torrefied sample	• Both studied factors and their interaction significantly involved solid yield. Temperature more affected the increment in HHV than residence time.	Abreu-Naranjo et al. (2018)
2-level factorial	*Pinus* wood pellets	• IP: temperature, duration time OP: solid yield	• Residence time had the strongest effect on mass yield in torrefaction. The satisfactory solid yield was obtained in short residence times and high temperatures or vice versa.	de Oliveira Brotto et al. (2022)
General factorial design	*J. curcas* seed cake	• IP: temperature, duration time OP: solid yield, HHV, and energy yield	• Torrefaction temperature was more superior factor to the duration. Temperature and time independently affected all three responses.	Madanayake et al. (2016)
Taguchi method	Sugarcane bagasse	• IP: microwave power, duration time, catalyst concentration OP: energy yield of torrefied sample	• Microwave power had the highest impact on energy yield, followed by duration and catalyst concentration.	Arpia et al. (2021)
Taguchi method	Methane and CO_2	• IP: GHSV, O_2/C, CO_2/O_2 OP: syngas yield	• First-stage optimization via the Taguchi approach suggested that the O_2/C was the most significant factor. GHSV had the most significant degree in the second-stage optimization from RSM.	Chen et al. (2021b)
Taguchi method	microalga *Chlorella vulgaris FSP-E*	• IP: microwave power, catalyst concentration, duration time OP: energy yield of torrefied sample	• Microwave power was the dominant parameter. Then catalyst concentration and duration followed.	Chen et al. (2022b)
Five-level fractional factorial design	*Picea abies* Karst.	• IP: torrefaction temperature, moisture content, particle size, pelletizing temperature OP: compression work, maximal force to overcome static friction, kinetic friction work, single pellet dimensions, and strength	• All tested factors significantly affected friction and compression work, pellet dimensions, and strength.	Rudolfsson et al. (2015)
Five-level fractional factorial design	*Pinus sylvestris* L.	• IP: torrefaction temperature, duration, moisture content, press channel lengths OP: power, fines, durability, moisture content, bulk density, grinding energy, water sorption pellet	• The most significant influence factors on the studied responses were ranked in the order of torrefaction temperature > torrefaction time > moisture contents > press channel lengths. The interactions of each input variable also affected the investigated output variables.	Rudolfsson et al. (2017)
Central composite design	eucalyptus	• IP: temperature, residence time OP: solid yield of torrefied sample	• The impact of both independent variables during torrefaction on solid yield had been remarkable Temperature affected the solid yield more than residence time	Singh et al. (2020b)
Central composite design	coffee grounds	• IP: torrefaction temperature, duration OP: solid yield of torrefied sample	• Torrefaction temperature was a dominant factor in production cost minimization.	Chai et al. (2016)
Central composite design	Herb residue	• IP: temperature and duration, herb residue moisture content, microwave power OP: solid and energy yield, energy consumption	• All four parameters affected microwave energy consumption Moisture content was the most crucial factor for all responses	Yan et al. (2021)
Central composite design	Red pine wood	• IP: torrefaction temperature, residence time OP: biocoal yield, energy yield, HHV, H/C and O/C ratios, Hardgrove grindability index	• Two independent parameters significantly influenced six responses. The optimal condition was obtained at approximately 300 °C and 30 min.	Keivani et al. (2018)
Box-Behnken design	sugarcane bagasse, pine sawdust, corn cob	• IP: temperature, time, blend ratio OP: solid yields, enhancement factors, HHV of coal, biomass, and waste-tire blends	• The significant effect of temperature over time and blending ratio was obtained.	Ozonoh et al. (2020)
Face-centred composite design	pigeon pea stalk	• IP: temperature, residence time, heating rate OP: HHV, energy yield of torrefied sample	• The temperature was the most significant operating parameter in responses. Duration and heating rate followed.	Singh et al. (2020a)
Face-centred composite design	*Acacia nilotica*	• IP: temperature, duration, heating rate OP: HHV and energy yield of torrefied sample	• Output variables were highly affected by temperature, while the minimal impact was found by heating rate and duration.	Singh et al. (2019)
2^2 factorial design	mesocarp fiber	• IP: time, reaction temperature OP: calorific value, weight loss, the energy yield of torrefied sample	• The energy yield of torrefied biomass was affected more by the temperature than by the duration.	Na et al. (2013)
ANOVA and pairwise t-test	*Pinus koraiensis*	• IP: atmosphere OP: yields and fuel properties of the torrefied sample	• The atmosphere insignificantly affected the yields and fuel properties of hydrochar products. The ash content gave an exception.	Nguyen et al. (2021)
ANOVA	Yard waste	• IP: temperature, carrier gas OP: mass yield, energy yield, HHV of torrefied sample	• The temperature had a more significant impact than carrier gas because rising temperature decreased solid and energy yields while increasing HHV.	Jaideep et al. (2021)
ANOVA	Switchgrass	• IP: partical size, temperature OP: water and oil sorption capacity	• The smallest particle sizes had the highest oil sorption capacity. Torrefied samples had lower water sorption capacities than raw samples. Torrefaction temperature did not have a statistically significant influence on oil sorption.	Tripathi et al. (2021)

is one of the valuable pathways in the RSM that has been commonly employed in torrefaction. This method estimates curvature using a fractional factorial design supplemented with axial points. The effects of operating parameters and optimal conditions on the investigated response (e.g., the HHV and solid and energy yields) are determined.

Singh et al. (2020b) used CCD to statistically comprehend the influence of two input variables (duration and temperature) on the torrefied eucalyptus yield. The precision of the acquired model was explained with an R^2 value > 0.95, suggesting that the model and the experimental data were highly correlated. The impact of both independent variables during torrefaction on solid yield had been remarkable, where temperature affected the solid yield more than residence time. Chai et al. (2016) also employed CCD with two operating parameters of torrefaction duration and temperature to conduct experiments. The integration of torrefaction and catalytic pyrolysis of coffee grounds produced benzene, toluene, ethylbenzene, and xylenes (BTEX), a green aromatic precursor of terephthalic acid. The regression model was adapted to forecast torrefaction mass yield because of high precision with an R^2 value of almost 0.99. The torrefaction conditions were optimized to minimize BTEX production cost at 239 °C and a duration of 34 min. Torrefaction temperature was a dominant factor in production cost minimization.

Yan et al. (2021) analyzed the combined effects of temperature, duration, herb residue's moisture content, and microwave power on solid and energy yields and microwave torrefaction energy consumption using CCD, and the significance of all input variables was conducted. Moreover, the optimal factor combination for microwave torrefaction was also evaluated. All four parameters affected microwave energy consumption, where moisture content was the most crucial factor for all responses. Moreover, the microwave torrefaction conditions were optimized at 225 °C temperature, 8.7 min residence time, 21.2 wt% moisture content, and 400 W microwave power.

Keivani et al. (2018) evaluated the combined effect of torrefaction temperature and duration using a quadratic model in the CCD technique. The two independent parameters significantly influenced six responses, including bio-coal yield, HHV, energy yield, H/C and O/C ratios, and Hardgrove grindability index. The optimal conditions were obtained at approximately 300 °C and 30 min.

4.2.2. Box-Behnken design (BBD)

The effects of experimental input variables on output variables and optimal conditions of the torrefaction process can be evaluated using the Box-Behnken design (BBD). This technique is beneficial in reducing time consumption and experimental runs.

Ozonoh et al. (2020) developed the model and optimized the torrefaction conditions considering duration, temperature, and blend ratio by employing RSM based on the BBD technique. Pine sawdust, sugarcane bagasse, and corn cob were employed as raw biomass materials in this study. The attained results were adopted to conduct torrefaction experiments. The solid yields, HHVs, and enhancement factors of coal, biomass, and waste-tire blends were determined as independent response variables. The results from the RSM regression analysis via the BBD technique demonstrated a significant effect of temperature over time and blending ratio.

4.3. Analysis of variance (ANOVA) and others

Regarding the RSM models mentioned above, face-centered composite design (FCCD) and full factorial design (FFD) are also useful in obtaining much information to conduct the relation between independent and response variables for evaluating a suitable experimental formulation. Moreover, analysis of variance (ANOVA) can be performed to examine the adequacy and fitness of the predicted models, and the significant parameters are selected based on the ANOVA results.

Nguyen et al. (2021) employed pairwise *t*-test and one-way ANOVA to evaluate the effects of different atmospheres on wet torrefaction. The results indicated that the atmosphere had an insignificant impact on hydrochar product yields and properties, but the ash content gave an exception. Jaideep et al. (2021) also used one-way ANOVA to determine the temperature and carrier gas effects on solid yield and HHV. The results showed a more pronounced influence of temperature than carrier gas. This was because a higher temperature decreased the solid and energy yields while the HHV increased. Tripathi et al. (2021) studied the water or oil sorbption ability of raw and torrefied switchgrass using ANOVA as a statistical test. They found that raw samples with the smallest particle sizes had the highest oil sorption capacity, whereas torrefied samples had notably lower water sorption capacities compared to raw samples.

Singh et al. (2020a) chose central face-centered (CCD) to analyze the optimum conditions of pigeon pea stalk torrefaction to establish the relationship between independent operating parameters and dependent response variables. The considered operating parameters comprised duration, temperature, and heating rate, and higher heating value and energy yield were regarded as dependent response variables. the predictions agreed well with the experimental data in that an R^2 value close to 1 was attained in their studied mathematical model. This suggested that the value of the responses could be predicted accurately. The most significant operating parameter on responses was temperature, and duration and heating rate followed. The optimum conditions for a maximum value of output variables were identified at 248 °C temperature, 60 min duration, and16.03 °C/min heating rate. Singh et al. (2019) also used a three-factor face central composite design to optimize HHV and energy yield of *Acacia nilotica* torrefaction. Process parameters of torrefaciton duration and duration and heating rate were studied to evaluate their impact on torrefaction performance. Temperature was highly affected to the system, while minimal impact was found by duration time and heating rate. The maximum value for both responses was temperature of 252 °C, duration of 60 min, and heating rate of 5 °C/min.

5. Challenge and future perspectives

For the challenge and future perspectives in this area, applying ML and statistical analysis with torrefaction is currently receiving a growing intention to increase model prediction performance. ML can generally predict the experimental data accurately, while statistical analysis can be used to design the experimental condition setup to obtain more robust and informative data. However, experimental data, suitable functions, and appropriate algorithms should be acquired before performing ML prediction. Statistical analysis can be used more easily, but its accuracy might be lower. ML and statistical analysis still face some barriers that reduce their potential. Those barriers may be divided into data accessibility, interpretability, and advanced algorithms. This section discusses the limitations and solutions of ML and statistical analysis.

First, data accessibility is a classical ML and statistical analysis problem when applied to bioenergy (Wang et al., 2021). It can be called lacking quality data, meaning the datasets for the ML results are non-homogeneous. For example, different feedstock properties (lignocellulosic biomass, microalgae, macroalgae, and animal manures), torrefaction reactor (fixed reactor, tube reactor, and fluidized reactor), and operating conditions (carrier gases, such as N_2, CO_2, and O_2, agent flow rate, temperature, and duration time) are causes of the ML potential in predictions. In addition, the statistical analysis needs a well-organized experimental design to fully obtain accurate data and a predictive model or response surface. To improve these problems, conducting and collecting more homogeneous experiments from classifying the homogeneous data should be undertaken and investigated.

Second, for interpretability, the ML and statistical analysis work as a black box-like model, which means it is limited to explaining the natural phenomena or behavior inside the box. The gray box model or the mechanistic model can then be used to enhance the comprehensibility of ML and statistical analysis. In this case, traditional models using chemical-physical mechanisms, including kinetic analysis, transfer mechanism, and thermodynamics approaches, should be used to support and enhance the capability of the current black box model in ML and statistical analysis.

Third, the new advanced computer and numerical algorithms, such as game theory and deep learning, can improve predictability and understanding. Also, a combination of qualitative and quantitative analysis may be conducted to get more accurate prediction results by characterizing each data group and correlating each data group. These will bring the data which have the same characteristic to predict together.

Moreover, the digital twin system and internet of things (IoT) could enhance predicting the performance of ML and SA of the torrefaction. Those technologies allowed an operator to interact and develop the process in real-time visualization. They could be applied in laboratory and pilot-scale torrefaction to optimize operation cost and system efficiency.

6. Conclusions

Machine learning methods and statistical analysis are superior to conventional models in reducing research time consumption and operation cost. It is therefore highly able to apply with the torrefaction process. ANNs are the most used in predicting system performance and properties. The statistical analysis explores the significant factors and their correlative behavior to achieve the optimal response. Combining theoretical models with kinetic study, transfer mechanism, thermodynamics, and statistical approaches can promote ML performance and reduce lacking quality data and black-box behavior. Game theory and deep learning algorithms are recommended to use with ML for new insights.

Declaration of Competing Interest

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

Data availability

The data that has been used is confidential.

Acknowledgments

This research was supported by a grant from the Faculty of Engineering at Kamphaeng Saen, Kasetsart University, Thailand. The authors also would like to acknowledge the financial support of the National Science and Technology Council, Taiwan, R.O.C., under the grant numbers MOST 109-2221-E-006-040-MY3, MOST 110-2622-E-006-001-CC1, and MOST 110-3116-F-006-003- for this research.

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