Renewable energy evaluation of recycled wood through thermochemical conversion pathway and artificial intelligence optimization: physicochemical, thermodegradation and flammability behaviours

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Context and objectives

Wood waste or byproducts have attracted international attention as a second-generation biofuel. The potential for renewable energy as a substitute for fossil fuels is regarded as one of the solutions to environmental and human health challenges created by fossil fuel combustion (Lin et al 2022). Wood waste is a possible feedstock for sustainable energy production (particularly bioenergy) obtained from lignocellulosic-based biomass (Petrissans et al. 2022). Hardwood species are composed of 38-51% cellulose, 17-38% hemicelluloses, 2-31% lignin, and 3% extractives. In contrast, softwood species consist of 2-3.5% extractives, 27-32% lignin, 22-40% hemicelluloses, and 33-42% cellulose. As a feasible technique for converting wood waste biomass into useful products like heat - combustion, one of the thermochemical processes (Fig. 1) is proposed. Moreover, several critical elements influence combustion, including temperature, heating rate, heating time, and fuel type. High CO emissions and the production of smoke or particulate matter (PM) might result from poorly managed combustion parameters. In this case, it is crucial to prevent incomplete combustion by evaluating the combustion parameter.

One useful method for assessing renewable energy in the circular bioeconomy concept from a biomass-based source is the specific chemical bioexergy (SCB) analysis type. The goal of SCB is to determine the energy of the biofuel based on the biomass' chemical composition (Chen and Aniza 2023). When compared to analyses based on lower heating values (LHV) or higher heating values (HHV), SCB offers a more thorough and in-depth evaluation that accurately captures the energy contained in biomass material. According to earlier research, exergy in biomass can be found by calculating the proximate analysis (ash content) and elemental analysis (C, H, O, N, and S elements) (Song et al 2013). In circular bioeconomy systems, thermodynamic inefficiencies (exergy destructions and losses) can be located, quantified, and caused by applying the SCB evaluation, which is based on the second law of thermodynamics on wood valorization. In order to achieve the future Sustainable Development Goals (SDGs) of the United Nations (SDGs) for cheap and clean energy (SDG 7), responsible consumption and production (SDG 12), and climate action (SDG 13), recycling woody debris into biofuel is thought to be an effective strategy. Furthermore, the objective of this study is closely associated with the ninth goal of industry, infrastructure, and innovation (SDG9) and the zero-waste principle for controlling waste production. By improving the scalability, affordability and dependability of renewable energy production and development, AI is employed to speed up the pace of the shift to a sustainable energy future.

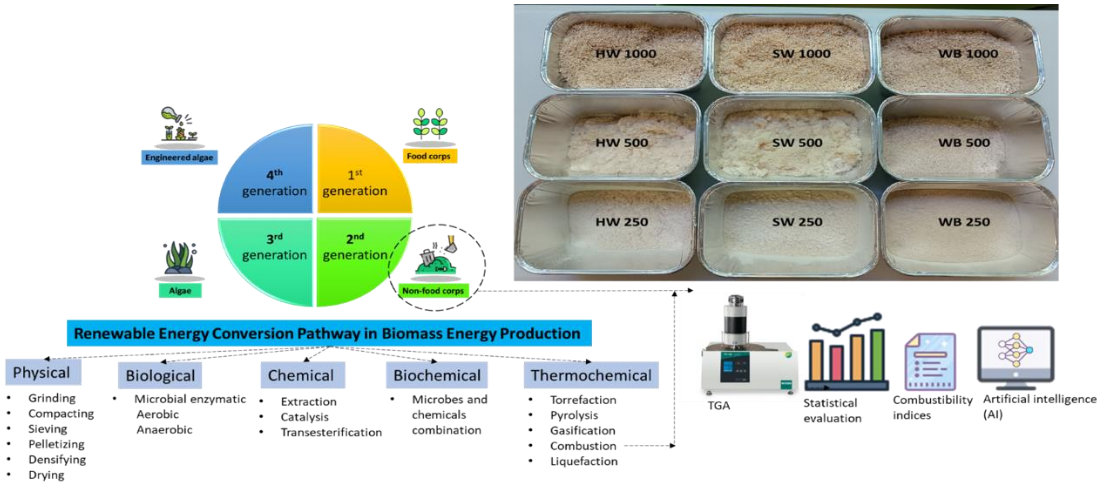

Fig. 1: Framework of renewable energy production through wood waste

To the best of the authors' knowledge, no study has, however, thoroughly examined the combustion of wood waste in terms of bioenergy (calorific value; HHV) and bioexergy (specific chemical biomass exergy; SCB), taking into account combustibility indexes and the application of AI. Additionally, little is known about the technology and development of this process. Consequently, the goal of this work is to give thorough TGA bioenergy and bioexergy evaluations of wood waste (Fig. 1). Physicochemical investigations characterize the qualities of wood waste feedstock. To ascertain the optimal amounts of desirable parameters and identify the influential aspects impacting performance, artificial neural networks (ANN) and statistical assessment (signal-to-noise ratio and analysis of variance) are employed in conjunction with AI analysis. Moreover, it provides industry experts and researchers with similar interests with useful information and a better understanding, especially for the development of renewable bioenergy production and industrial scale-up employing bioenergy woody-based products.

Material and methods

For use in the timber industries, the nearby forest's woods (hardwood: beech *Fagus sylvatica*, and softwood: fir *Abies alba*) were collected. Hardwood (HW), softwood (SW), and wood blend (WB, a 50-50 weight percentage combination of HW and SW) were the three waste categories into which the samples were divided. The WB combination followed the recommendation of Forest Stewardship Council (FSC) in the European Union (EU) region for solid biofuel with a 50-50 weight percentage mixture of HW and SW.

Sample preparation and design of experiment

The samples underwent a 24-hour sun-drying process outside. In order to achieve a consistent particle size across three sizes—250, 500, and 1000 µm—the dry samples were separately ground and sieved (Aniza et al. 2022). Furthermore, three distinct levels are assigned to each of these factors: (1) hardwood, softwood, and wood blend (HW, SW, and WB); (2) 250, 500, and 1000 µm; and (3) 10, 15, and 20 °C·min^{-1}. Nine runs (L9) of experiments comprised the design matrix with the three components and three design levels.

Physicochemical and statistical evaluations

The samples were examined for their proximate analysis (PA), elemental analysis (EA), calorific values (HHV) and FTIR. The thermodegradation behavior was identified by using the TGA method. The SCB calculation was carried out as follows (Song et al 2013):

$$SCB = 36.3439\,C + 107.5633\,H - 8.6308\,O + 0.4147\,N + 19.0798\,S - 21.100\,A \quad \text{(Eq.1)}$$

where C, H, O, N, S, and A denoted carbon, hydrogen, nitrogen, sulfur, and ash, respectively. The TG apparatus NETZSCH – STA 449 F3 Jupiter was used to directly burn wood waste. A ceramic crucible with a capacity of approximately 90 µL was filled with 5 mg of the sample. For example, the N_2 gas was purged into the system for five minutes at a rate of 100 mL·min^{-1}. Subsequently, three heating rates were applied to the sample: 10, 15, and 20 °C·min^{-1}, from room temperature to 800 °C (Fig. 2). The amount of solid that remained in the crucible was called the ash content. The PA, EA, HHV, and direct combustion experiments in this study were all carried out in duplicate. With a maximum risk of 5%, the data's repeatability was maintained at >95%.

Flammability indexes and artificial intelligence analysis

The ignition index Dig (%·min^{-3}) was calculated according to López-González et al. (2017) as follows:

$$D_{ig} = \frac{(\mathrm{d}w/\mathrm{d}t)_{max}}{(t_{max} \cdot t_{ig})} \quad \text{(Eq. 2)}$$

where t_{ig} was the ignition time, t_{max} is the time corresponding to the maximum combustion rate $(\mathrm{d}w/\mathrm{d}t)_{max}$ and $(\mathrm{d}w/\mathrm{d}t)_{max}$ (%·min^{-1}) is the maximum combustion rate (DTG curve at the highest peak - DTGmax). By showing the fuels' propensity to absorb heat and start burning, the ignition index suggested that collected fine fuels may ignite in the presence of a heat source. Additionally, the artificial neural network (ANN) analysis was utilized in this work to forecast the SCB and HHV values. In order to ascertain the impact of the HHV and SCB as the output data, the parameters were created as input data. The duplicate Taguchi parameters (waste type, particle size, and heating rate–9 runs): 18 data, EA (C–H–O): 18 data (HW, SW, and WB), and PA (M, VM, FC, Ash): 24 data (HW, SW, and WB) are among the ten parameters that were utilized to feed the input data. Megaputer Polyanalyst 6.5 was the program used to create the ANN model.

Results and discussion

Characterization analysis

HW, SW, and WB moisture contents for proximate analysis are 5.94, 4.00, and 3.00 wt%, respectively (Tab. 1). Biofuel's low moisture content is advantageous since it may boost energy density and enhance combustion efficiency. All samples, including HW (84.05 wt%), SW (83.50 wt%), and WB (83.67 wt%), have VM values higher than 80wt%. A high VM in the sample means that there is a good chance that solid chemical molecules, such as cellulose, lignin, and hemicelluloses, will devolatilize into gaseous chemical compounds. As a result, the word S and the ash content in Eq. (1) about the SCB computation may be removed. Tab. 1 indicates that, out of all samples (WB – HHV: 19.32 MJ·kg^{-1}, SCB: 18.52 MJ·kg^{-1} and HW – HHV: 19.03 MJ·kg^{-1} and SCB: 18.20 MJ·kg^{-1}), SW had the highest HHV and SCB values

(HHV: 18.84 MJ·kg-1, SCB: 19.65 MJ·kg^{-1}). The reason for these phenomena is that the C-element content of the SW is larger (C: 47.26 wt%) than that of WB (C: 46.58 wt%) or HW (C: 45.99 wt%). The amount of H-element in the samples is found to be extremely low (approximately <6 wt%), even though it has the largest coefficient value in the SCB determination (Eq. 1). As a result, the HHV and SCB values of wood waste samples are not substantially affected by the H-element.

Tab. 1. Properties of raw wood waste: PA, EA, HHV, and SCB

Biomass properties	***HW***	***SW***	***WB***
Proximate (wt%)			
M	5.94	4.00	3.00
VM	84.05	83.50	83.67
FC	10.00	12.50	13.32
Ash	<0.01	<0.01	0.01
Elemental (wt%)			
C	45.99	47.26	46.58
H	5.77	5.86	5.86
O	45.05	44.36	45.32
N	< 0.05	< 0.05	< 0.05
S	< 0.05	< 0.05	< 0.05
Bioenergy-HHV and bioerxergy-SCB (MJ·kg^{-1})			
HHV	18.20	18.84	18.52
SCB	19.03	19.65	19.32
SCB/HHV ratio	1.046	1.043	1.043

The thermodegradation behavior of wood waste is evaluated through the TGA method (Fig. 2). The first peak relates to the thermodegradation of lignocellulosic chemical complexes with light molecular weight (hemicelluloses) and some lignin. Some previous experiments showed that the hemicelluloses from lignocellulosic biomass mostly degraded, not surpassing 275 °C (Escalante et al. 2022). The second peak has the highest peak among the others. This peak (300-400 °C) relates to the thermodegradation of mostly cellulose and some lignin. Simultaneously, the third peak appears at about 450-550 °C, demonstrating the thermodegradation from a slight cellulose and the rest of the lignin.

Flammability index and chemical functional group

A high ignition index (Fig. 3) at the same heating rate means that the material will ignite at lower temperatures. This characteristic means that the material requires less energy or heat than materials with lower ignition indices to start the ignition process. Furthermore, the criterion of self-ignition is divided into four classes: non-reactive (Dig 0.00-0.02), low-reactive (Dig 0.021-0.03), reactive (Dig 0.031-0.05), and high-reactive (>0.051). The results indicate that waste wood is classified into three regions non-, low-, and reactive. The highly reactive biofuel (>0.051) is not suggested due to safety concerns (fire, explosion), handling challenges (transporting, storing, packaging), and environmental impacts (air pollution). In this regard, wood waste is considered as a decent biofuel feedstock. The functional group of chemical compounds has been identified by FTIR test. The 1st peak at 1,158.50 cm^{-1} appears in a range of wavenumber about 1,120 – 1,160 cm^{-1} corresponding to the C-O-C polysaccharide functional group. The C-O-C asymmetric stretching functional group of the 1st peak at 1,158.50 cm^{-1} in the range of wavenumber about 1,120 – 1,160 cm^{-1} is associated with the chemical compound in cellulose (Emmanuel et al. 2015) and the mannose group of hemicelluloses (Horikawa et al

2019). The mannan-type hemicellulose group (mannose) is a polysaccharide composed of six-carbon sugar glucose. Softwood mannose can be found as the most abundant sugar compared to other polysaccharide groups. The asymmetric CH_2 stretching vibration is classified as methylene and methine groups in the 2nd peak. The CH_2 functional group in the 2nd peak is noticeable at 2,948.63 cm^{-1} in the wave number of 2,850 – 2,950 cm^{-1}, correlated to the two types of hemicelluloses (xylan and mannose), cellulose, and lignin (Li et al 2018). Furthermore, the 3rd peak is acknowledged at 3,425.40 cm-1 which is assigned to the OH molecules. The OH molecules stretching absorption bends are typically absorbed in about 3400 cm^{-1} wave number (3,350 – 3,450 cm^{-1}), associated with cellulose and hemicelluloses (Sharma et al 2024).

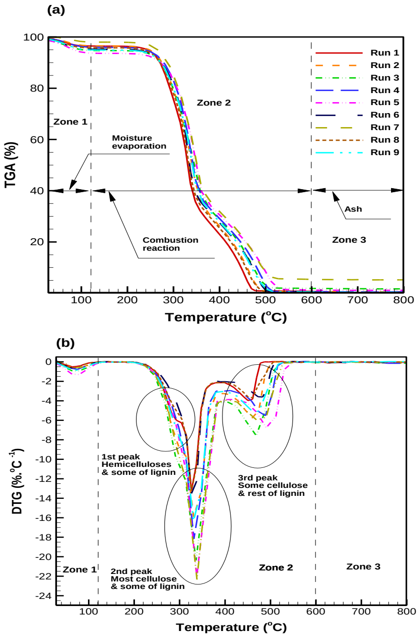

Fig. 2. Thermodegradation behavior of hardwood, softwood, and wood blends respected to (a) TGA and (b) DTG curvatures.

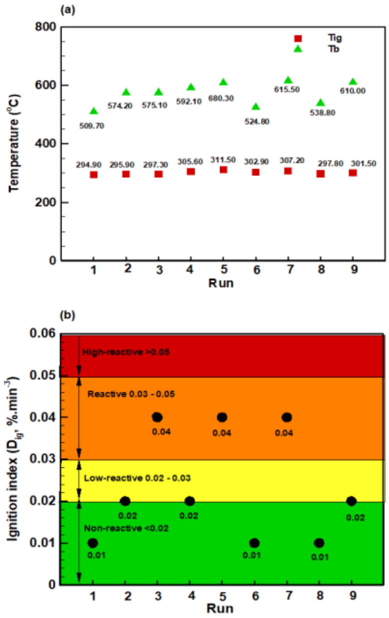

Fig. 3. Profile of (a) ignition and burnout temperature and (b) ignition index of wood waste.

Prediction by ANN model

Among the configurations, the best result of the ANN model for HHV and SCB model predictions with the lowest standard deviation is obtained by utilizing a 1 HL with 5 N for HHV with the fit quality precisely R^2= 1. In this regard, the wood waste type is the most influence factor in bioenergy analysis (HHV), followed by FC, O, C, H particle size, A, heating rate, VM and M. Likewise, the configuration of 1HL with 5N illustrates the best result prediction for the bioexergy analysis (SCB). The most influential parameters are wood waste type, followed by H, FC, C, O, A, particle size, heating rate, M, and VM.

Conclusions

This study investigated the combustibility thermodegradation behavior of wood wastes (HW, SW, and WB) using the TGA method in conjunction with the Taguchi orthogonal, statistical analysis, combustibility indices, and AI model predictions. The physicochemical tests reveal that all wood waste feedstock is high in VM (>80 wt%), high in C and O, and low in ash, N, and S. The evaluation shows that the SCB is typically higher (about > 19 MJ·kg^{-1}) than HHV (about 18 MJ·kg^{-1}). The TGA/DTG curves obtained, using typical heating rates of 10, 15, and 20 °C·min^{-1}, suggest there are 3 zones distinguished. The combustibility indexes indicate that wood waste has 4 classes of ignition index (non-reactive to high-reactive). The optimum run is achieved with SW250 at 20 °C·min^{-1} heating rate. The ANN model with 1HL–5N configuration successfully predicts the values of HHV and SCB with excellent fit-quality values (R^2=1).

Acknowledgments

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