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Thermal decomposition of rice husk: a comprehensive artificial intelligence predictive model

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Abstract

This study explored the predictive modelling of the pyrolysis of rice husk to determine the thermal degradation mechanism of rice husk. The study can ensure proper modelling and design of the system, towards optimising the industrial processes. The pyrolysis of rice husk was studied at 10, 15 and 20 °C min^{-1} heating rates in the presence of nitrogen using thermogravimetric analysis technique between room temperature and 800 °C. The thermal decomposition shows the presence of hemicellulose and some part of cellulose at 225–337 °C, the remaining cellulose and some part of lignin were degraded at 332–380 °C, and lignin was degraded completely at 480 °C. The predictive capability of artificial neural network model was studied using different architecture by varying the number of hidden neurone node, learning algorithm, hidden and output layer transfer functions. The residual mass, initial degradation temperature and thermal degradation rate at the end of the experiment increased with an increase in the heating rate. Levenberg–Marquardt algorithm performed better than scaled conjugate gradient learning algorithm. This result shows that rice husk degradation is best described using nonlinear model rather than linear model. For hidden and output layer transfer functions, ‘log-sigmoid and tan-sigmoid', and ‘tan-sigmoid and tan-sigmoid' transfer functions showed remarkable results based on the coefficient of determination and root mean square error values. The accuracy of the results increases with an increasing number of hidden neurone. This result validates the suitability of an artificial neural network model in predicting the devolatilisation behaviour of biomass.

References

1. 1.

   Wu X, Wu Y, Wu K, Chen Y, Hu H, Yang M. Study on pyrolytic kinetics and behavior: the co-pyrolysis of microalgae and polypropylene. Bioresour Technol. 2015;192:522.

   CAS Article Google Scholar

2. 2.

   Chen W-H, Lin B-J, Huang M-Y, Chang J-S. Thermochemical conversion of microalgal biomass into biofuels: a review. Bioresour Technol. 2015;184:314.

   CAS Article Google Scholar

3. 3.

   Özçimen D, Karaosmanoğlu F. Production and characterization of bio-oil and biochar from rapeseed cake. Renew Energy. 2004;29(5):779.

Article **Google Scholar**

4. 4.

   Li Z, Zhao W, Meng B, Liu C, Zhu Q, Zhao G. Kinetic study of corn straw pyrolysis: comparison of two different three-pseudocomponent models. Bioresour Technol. 2008;99(16):7616.

   CAS **Article** **Google Scholar**

5. 5.

   Park HJ, Park Y-K, Dong J-I, Kim J-S, Jeon J-K, Kim S-S, Kim J, Song B, Park J, Lee K-J. Pyrolysis characteristics of Oriental white oak: kinetic study and fast pyrolysis in a fluidized bed with an improved reaction system. Fuel Process Technol. 2009;90(2):186.

   CAS **Article** **Google Scholar**

6. 6.

   Yao X, Xu K, Liang Y. Comparing the thermo-physical properties of rice husk and rice straw as feedstock for thermochemical conversion and characterization of their waste ashes from combustion. BioResources. 2016;11(4):10549.

   Google Scholar

7. 7.

   Sfakiotakis S, Vamvuka D. Development of a modified independent parallel reactions kinetic model and comparison with the distributed activation energy model for the pyrolysis of a wide variety of biomass fuels. Bioresour Technol. 2015;197:434.

CAS Article Google Scholar

8. 8.

Di Blasi C. Modeling chemical and physical processes of wood and biomass pyrolysis. Prog Energy Combust Sci. 2008;34(1):47.

Article Google Scholar

9. 9.

Alaba PA, Sani YM, Daud WMAW. A comparative study on thermal decomposition behavior of biodiesel samples produced from shea butter over micro-and mesoporous ZSM-5 zeolites using different kinetic models. J Therm Anal Calorim. 2016;126(2):943.

CAS Article Google Scholar

10. 10.

Damartzis T, Vamvuka D, Sfakiotakis S, Zabaniotou A. Thermal degradation studies and kinetic modeling of cardoon (*Cynara cardunculus*) pyrolysis using thermogravimetric analysis (TGA). Bioresour Technol. 2011;102(10):6230.

CAS Article Google Scholar

11. 11.

Becidan M, Várhegyi G, Hustad JE, Skreiberg Ø. Thermal decomposition of biomass wastes. A kinetic study. Ind Eng Chem Res. 2007;46(8):2428.

CAS Article Google Scholar

12.12.

Várhegyi G, Bobály B, Jakab E, Chen H. Thermogravimetric study of biomass pyrolysis kinetics. A distributed activation energy model with prediction tests. Energy Fuels. 2010;25(1):24.

Article Google Scholar

13.13.

Gašparovič L, Labovský J, Markoš J, Jelemenský L. Calculation of kinetic parameters of the thermal decomposition of wood by distributed activation energy model (DAEM). Chem Biochem Eng Q. 2012;26(1):45.

Google Scholar

14.14.

White JE, Catallo WJ, Legendre BL. Biomass pyrolysis kinetics: a comparative critical review with relevant agricultural residue case studies. J Anal Appl Pyrolysis. 2011;91(1):1.

CAS Article Google Scholar

15.15.

Alaba PA, Abbas A, Huang J, Daud WMAW. Molybdenum carbide nanoparticle: understanding the surface properties and reaction mechanism for energy production towards a sustainable future. Renew Sustain Energy Rev. 2018;91:287.

CAS Article Google Scholar

16.16.

Magela E, Silva G, Acioli PH, Pedroza AC. Estimating correlation energy of diatomic molecules and atoms with neural networks. J Comput Chem. 1997;18(11):1407.

Article **Google Scholar**

17.17.

Balabin RM, Lomakina EI. Neural network approach to quantum-chemistry data: accurate prediction of density functional theory energies. J Chem Phys. 2009;131(7):074104.

Article **Google Scholar**

18.18.

Urata S, Takada A, Uchimaru T, Chandra AK, Sekiya A. Artificial neural network study for the estimation of the C–H bond dissociation enthalpies. J Fluor Chem. 2002;116(2):163.

CAS **Article** **Google Scholar**

19.19.

Duan X-M, Li Z-H, Song G-L, Wang W-N, Chen G-H, Fan K-N. Neural network correction for heats of formation with a larger experimental training set and new descriptors. Chem Phys Lett. 2005;410(1–3):125.

CAS **Article** **Google Scholar**

20.20.

Wu J, Xu X. Improving the B3LYP bond energies by using the X 1 method. J Chem Phys. 2008;129(16):164103.

Article Google Scholar

21.21.

Alaba PA, Popoola SI, Olatomiwa L, Akanle MB, Ohunakin OS, Adetiba E, Alex OD, Atayero AA, Daud WMAW. Towards a more efficient and cost-sensitive extreme learning machine: a state-of-the-art review of recent trend. Neurocomputing. 2019;350:70.

Article Google Scholar

22.22.

Behler J. Neural network potential-energy surfaces in chemistry: a tool for large-scale simulations. Phys Chem Chem Phys. 2011;13(40):17930.

CAS Article Google Scholar

23.23.

Mohammed IY, Abakr YA, Hui JNX, Alaba PA, Morris KI, Ibrahim MD. Recovery of clean energy precursors from Bambara groundnut waste via pyrolysis: kinetics, products distribution and optimisation using response surface methodology. J Clean Prod. 2017;164:1430.

CAS Article Google Scholar

24.24.

Mohammed IY, Abakr YA, Yusup S, Alaba PA, Morris KI, Sani YM, Kazi FK. Upgrading of Napier grass pyrolytic oil using microporous and hierarchical mesoporous zeolites: products distribution, composition and reaction pathways. J Clean Prod. 2017;162:817.

CAS **Article** **Google Scholar**

25.25.

Szumera M, Wacławska I, Sułowska J. Thermal properties of MnO_2 and SiO_2 containing phosphate glasses. J Therm Anal Calorim. 2016;123(2):1083.

CAS **Article** **Google Scholar**

26.26.

Noh J, Back S, Kim J, Jung Y. Active learning with non-ab initio input features toward efficient CO_2 reduction catalysts. Chem Sci. 2018;9(23):5152.

CAS **Article** **Google Scholar**

27.27.

Azarmi S, Oladipo A, Vaziri R, Alipour H. Comparative modelling and artificial neural network inspired prediction of waste generation rates of hospitality industry: the case of North Cyprus. Sustainability. 2018;10(9):2965.

Article **Google Scholar**

28.28.

Betiku E, Ajala SO. Modeling and optimization of *Thevetia peruviana* (yellow oleander) oil biodiesel synthesis via *Musa paradisiacal* (plantain) peels as heterogeneous base catalyst: a case of artificial neural network vs. response surface methodology. Ind Crops Prod. 2014;53:314.

CAS **Article** **Google Scholar**

29.29.

Møller MF. A scaled conjugate gradient algorithm for fast supervised learning. Neural Netw. 1993;6(4):525.

Article **Google Scholar**

30.30.

Du Y-C, Stephanus A. Levenberg–Marquardt neural network algorithm for degree of arteriovenous fistula stenosis classification using a dual optical photoplethysmography sensor. Sensors. 2018;18(7):2322.

Article **Google Scholar**

31.31.

Hagan MT, Menhaj MB. Training feedforward networks with the Marquardt algorithm. IEEE Trans Neural Netw. 1994;5(6):989.

CAS **Article** **Google Scholar**

32.32.

Cömert Z, Kocamaz AF. A study of artificial neural network training algorithms for classification of cardiotocography signals. Bitlis Eren Univ J Sci Technol. 2017;7(2):93.

Article **Google Scholar**

33.33.

Popoola SI, Adetiba E, Atayero AA, Faruk N, Calafate CT. Optimal model for path loss predictions using feed-forward neural networks. Cogent Eng. 2018;5(1):1444345.

Article **Google Scholar**

34.34.

Kuprianov VI, Arromdee P. Combustion of peanut and tamarind shells in a conical fluidized-bed combustor: a comparative study. Bioresour Technol. 2013;140:199.

CAS **Article** **Google Scholar**

35.35.

Isa KM, Daud S, Hamidin N, Ismail K, Saad SA, Kasim FH. Thermogravimetric analysis and the optimisation of bio-oil yield from fixed-bed pyrolysis of rice husk using response surface methodology (RSM). Ind Crops Prod. 2011;33(2):481.

CAS **Article** **Google Scholar**

36.36.

Mansaray K, Ghaly A. Thermal degradation of rice husks in nitrogen atmosphere. Bioresour Technol. 1998;65(1–2):13.

CAS **Article** **Google Scholar**

37.37.

Azizi K, Moraveji MK, Najafabadi HA. Characteristics and kinetics study of simultaneous pyrolysis of microalgae *Chlorella vulgaris*, wood and polypropylene through TGA. Bioresour Technol. 2017;243:481.

CAS Article Google Scholar

38.38.

Chen C, Ma X, He Y. Co-pyrolysis characteristics of microalgae *Chlorella vulgaris* and coal through TGA. Bioresour Technol. 2012;117:264.

CAS Article Google Scholar

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